British Journal of Interdisciplinary Research August 2026, Volume 3, Number 13, pp. 14-36
ISSN 3049-8899

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING ON OPERATIONAL DECISION-MAKING (POST-PANDEMIC): A STUDY OF MULTINATIONAL COMPANY, ABUJA, NIGERIA

Momoh Blessing Fatima,

Department of Business Administration, University of Abuja,

fsbmomoh@gmail.com

&

Theresa I. Ndulue,

Department of Business Administration, University of Abuja

nduluetheresa@yahoo.com

Abstract

Multinational organisations such as Nestlé Nigeria Plc, Abuja, faced immense difficulties in the post-pandemic operating environment, especially in the need to ensure that decision making is accurate and quick to maintain efficiency and competitiveness. This study looked at the influence of Artificial Intelligence and machine learning on operational decision making, specifically on the use of AI driven predictive analytics, and AI based decision support systems. The descriptive research was used and a population of 496 managerial and operational staff who directly participate in decision making was identified while the sample of 269 respondents was obtained using the Yamane's formula with a 20% margin of error. Stratified sampling was used to include production managers, officers of the supply chain, inventory controllers, and logistics coordinators in a representative sample. Structured questionnaires were used for data collection, and expert review was used to validate content and Cronbach's alpha was used to validate reliability with coefficients of 0.87 for predictive analytics, 0.85 for decision support systems, 0.82 for decision accuracy, and 0.80 for decision speed. The results of the regression analysis carried out with SPSS v27 showed that the use of predictive analytics significantly increased the accuracy of the decision (H_{01} rejected), while the use of AI based decision-support systems significantly improved the speed of the decision (H_{02} rejected). The study findings showed that the use of AI & ML significantly enhanced decision making for the organisation, Nestlé Nigeria Plc; thus, the researchers recommended that Nestlé Nigeria Plc should continue investing in and implementing the technology of predictive analytics tools and decision support systems to ensure that decisions are made optimally and accurately in the future within the company.

Keywords: *Artificial Intelligence, Machine Learning, Predictive Analytics, Decision-Support Systems, Operational Decision-Making, Accuracy, Speed.*

DOI: 10.31039/bjir.v3i13.148

1. INTRODUCTION

AI and machine learning have gone beyond the realm of niche technical concepts and become tools of organizational intelligence. Around the globe, companies are facing markets in which demand fluctuates rapidly, supply chains are highly vulnerable, consumer behavior is increasingly digital, and manager decisions have to be made quicker and more accurately. This increased pressure was exacerbated by the COVID-19 pandemic. It revealed the problems with the traditional planning process, particularly when relying on over-reliance on past routines, manual reporting, lack of timely information and managerial intuition. In such a setting, AI and machine learning became more appealing, as they enabled organisations to scan through vast amounts of data, discern patterns, predict future scenarios, and aid in decision-making actions in advance of operational issues. The change is evident throughout the supply chain analytics, production resiliency, risk reduction, forecasting, and organisational decision processes, where capabilities enabled by AI have increasingly been associated with improved speed and quality of decisions (Aylett-Bullock et al., 2020; Dubey et al., 2021; Drydakis, 2022; Neiroukh et al., 2024).

AI can be seen as the ability of computer-based systems to carry out tasks, typically associated with the capabilities of human intelligence, including learning, reasoning, pattern recognition, prediction, and recommendations. Machine learning is a specific type of AI which is more directly concerned with algorithms used for learning from data and for improving their output in response to the subsequent inputs of relevant data. Many decisions in modern organizations are no longer based on an isolated experience and in operational decision making this is an excellent tool. These are based on production records, sales information, inventory movements, customer demand trends, supplier actions, logistics data, and market signals. For a global food and beverage company like Nestlé, this can translate to helping with product availability, demand forecasting, distribution, stock replenishment, quality control, procurement timings, route optimisation and resource allocation. AI, machine learning, data science and predictive analytics are mentioned as tools that can help Nestlé's engineers, designers and operators to gain insights faster, as part of its global digital innovation agenda, and as part of its sustainability reporting, AI, predictive analytics, monitoring and trend analysis are described as ways to help achieve efficiency and results (Nestlé, 2023, 2024).

In this research, the first fundamental aspect of AI and machine learning is AI-based predictive analytics and forecasting. This dimension relates to the application of AI and machine learning models to analyze past and real-time data to predict future events—including consumer demand, supply constraints, sales fluctuations, production demands, distribution pressure, and more. This dimension is now more relevant in the post-pandemic as demand has not always been regular and predictable. A firm can forecast its inventory of a product based on sales for the previous month, but if the buying power, transportation expenses, foreign currency exchange rate, or consumer demand for the product changes abruptly, the forecast may be invalid. One way to mitigate this is to use artificial intelligence, which can help to identify trends that might not be apparent through traditional manual methods. This could be a lifesaver for Nestlé Nigeria Plc, Abuja, in predicting product demand at its outlets, catering to distributors to avoid stock-outs, avoiding overstocking, and making better operational decisions. AI-driven supply chain analytics during the pandemic has also highlighted the importance of analytics capability to help organizations navigate uncertainty and adapt to disruption in their operations (Dubey et al., 2021; Dohale et al., 2022).

The second dimension is the AI-powered decision support. Unlike predictive analytics, which is mostly concerned with what may happen, decision support systems can assist the manager with understanding what information is available and employing suitable action. They can be presented in the form of dashboards, alerts, automatic recommendations, maintenance warnings, scenario analysis tools or performance monitoring platforms. In real life, they don't eliminate the role of human intelligence. Instead, they provide organised evidence which enables managers to make informed decisions. It is particularly helpful in multi-national firms where the decision-making process can take place at multiple operational levels such as sales, warehouses, procurement, logistics, finance and customer service. AI-driven decision support systems might aid managers at Nestlé Nigeria Plc, Abuja, in identifying slow-moving stock swiftly, evaluating distributor efficiency, addressing supply delays rapidly, prioritizing urgent operational tasks, and tracking demand fluctuations at various sites. In response, Chen et al. (2021) introduced an AI-based Human-centric Decision Support as a valuable framework for making prompt and informed decisions during a pandemic and Neiroukh et al. (2024) associated AI capability with the speed of decisions and with decision quality for organisational performance.

Operational decision making is the set of short to medium time decisions that an organisation makes to ensure that it operates effectively and efficiently day-to-day. It's not simply high level strategy. It's about questions like how many to make, when to order more, how to divide up resources, how to handle missed deliveries, which risk in operation needs addressing, and how quickly business managers should react when conditions in the market change. In a company like Nestlé Nigeria Plc, Abuja, decisions to be made in a business will include co-ordinating product flow, sales information, distributor requirements, inventory management, customer requirements and internal reporting. In this study, accuracy and speed are the two most important operational aspects of decision-making. Accuracy means decisions are correct, reliable, evidence based and can minimize the errors in planning, stock control, distribution and resource utilization. Speed is the timely processing of information and timely action by managers. The right decision may be made too late to avoid a stock-out, and the wrong decision may be made too quickly, if it is based on incomplete or insufficient information. The real key to the utility of operational decision making is to get the decision right, but not too late.

In the context of operational decisions, a combination of artificial intelligence, machine learning, and data analysis has the potential to play a significant role in the future of Nestlé Nigeria Plc, Abuja.The use of AI, machine learning, and data analysis in operational decision-making is a complex interplay that requires some cautious consideration. By leveraging AI-powered predictive analytics, managers can make more accurate operational decisions, as the technology can predict demand, detect risk patterns, and minimize uncertainty in planning. An AI-powered decision-support system can help speed up the process of making decisions during operations by turning complex data into insights, alerts, and recommendations. Nevertheless, this relationship should not be assumed as it is not automatic. AI can help with decision making, but only if the organisation has the right data, has the right people, has the right technology, has the right attitudes and environment, and the right management. In this regard, AI and machine learning may not just be a utility to “improve” operational decision-making by itself; rather, it may be a tool that enables managers at Nestlé Nigeria Plc, Abuja, to make quicker and more accurate decisions in a post-pandemic operating context, if and when the technology is properly integrated with the human and organisational processes (Drydakis, 2022; Rajagopal et al., 2022; Neiroukh et al., 2024).

Statement of the Problem

Decision making in an ideal post-pandemic business environment was to be quick, accurate, data-driven, and responsive to market changes in a multinational food and beverage company. This was where Nestlé Nigeria Plc, Abuja could have relied on AI-driven predictive analytics and AI-based decision-making systems to forecast demand, inform inventory planning, minimize operational mistakes, and quickly address distribution, procurement, and customer-service demands.

However, such an ideal state was practically challenged by the Nigerian operational environment. Following the pandemic, firms in the consumer goods sector experienced continued price volatility, declining purchasing power of consumers, foreign exchange and energy prices, and supply-chain disruptions. The headline inflation for the nation increased to 34.19% in June 2024 while the food inflation rose to 40.87% (National Bureau of Statistics [NBS], 2024). This is a challenging planning horizon for firms involved in food product, raw material, logistics and retail demand. In these cases, decisions based primarily on manual reporting, outdated data or management experience were likely to be inaccurate and take time to react. This could have impacted demand forecasting, stock availability, routing, replenishment and timely managerial response among other areas for Nestlé Nigeria Plc, Abuja.

There has already been a number of empirical studies about the capacity of AI, analytics of the supply chain, resilience to production, and decision support systems in a wide organisational and in a pandemic context (Dubey et al., 2021; Dohale et al., 2022; Neiroukh et al., 2024). However, little consideration had been paid to the computational speed of the AI-based decision support system with relation to the speed of decision-making and the accuracy of the decision made with the aid of AI-based predictive analytics in a Nigerian multi-national food and drink company context. This led to a contextual and empirical gap which necessitated the present study, especially the study of the realities of post pandemic operational decision making of Nestlé Nigeria Plc, Abuja.

Research Questions

Based on the problems identified in the post-pandemic operational environment, the following research questions are formulated to investigate how AI and machine learning affect decision-making at Nestlé Nigeria Plc.

i. How does the use of predictive analytics and forecasting impact the accuracy of operational decisions at Nestlé Nigeria Plc?

ii. In what ways do AI-based decision-support systems influence the speed of operational decision-making in the company?

Broad Objective

The main objective of the study is to examine the impact of artificial intelligence and machine learning adoption on operational decision-making in Nestlé Nigeria Plc, Abuja. Specifically, the objectives are to:

i. assess the effect of AI-driven predictive analytics and forecasting on the accuracy of operational decisions at Nestlé Nigeria Plc.

ii. determine the influence of AI-based decision-support systems on the speed of operational decision-making within the organisation.

Statement of Hypotheses

To provide a testable basis for empirical investigation, the study proposes the following null hypotheses:

H_{01}: Predictive analytics and forecasting have no significant effect on the accuracy of operational decisions at Nestlé Nigeria Plc.

H_{02}: AI-based decision-support systems have no significant effect on the speed of operational decision-making at Nestlé Nigeria Plc.

Scope of the Study

The study focuses on the Artificial Intelligence and machine learning on operational decision-making (post-pandemic): a study of Nestlé Nigeria Plc, Abuja. The geographical location for the study was selected to be Abuja because it serves as the operational and administrative headquarters of Nestlé Nigeria, where the headquarters and coordinating activities of the company are located. The selection of Nestlé Nigeria Plc was based on its status as a prominent multinational company in the food and beverage industry in Nigeria, thus making it an ideal case to study the use of AI and machine learning in decision making processes in operations. For reasons of their well-known importance in predicting demand, in generating actionable information or increasing the reliability of decision-making in post-pandemic settings, Artificial Intelligence and machine learning were proxied by AI-driven predictive analytics and AI-based decision-support systems (Neiroukh et al., 2024; Chen et al., 2021). Operational decision making was used as a proxy for the dependent variable, accuracy and speed, widely accepted dimensions of the quality and timeliness of managerial and operational decisions in complex organisational settings (Dohale et al., 2022; Dubey et al., 2021). Therefore, this study was targeted at the extent to which the selected AI/ML dimensions can improve managerial effectiveness and responsiveness in Nestlé Nigeria Plc, Abuja as they are interwoven with the operational decision-making dimensions.

2. LITERATURE REVIEW

Conceptual Framework

Concept of Artificial Intelligence and Machine Learning

Artificial Intelligence (AI) and machine learning (ML) have gradually evolved from somewhat obscure technologies to essential tools within the business and an integral part of the organisation with the capacity to change the way decisions are made in complex environments. In general, AI is the technology of computers that imitate human intelligence for analysing or interpreting data and solving problems. Machine learning is more a focus on the system learning from data patterns and improving its performance over time. Traditional managerial processes were found to be ineffective when dealing with the amount and velocity of operational data in the post-pandemic business scene, which is where AI and ML come into the picture and become an essential tool for maintaining competitive advantage (Neiroukh et al., 2024; Khan, 2025). In this regard, organisations are increasingly turning to these technologies not just for automation, but to gain a predictive view, analyze various scenarios and optimise decisions, enabling managers to be able to act proactively to face disruptions, predict customer needs and allocate resources in an efficient way.

In the day-to-day, AI and ML enable data-driven operational planning, lessen the need for gut feeling, and offer structured recommendations. With Nestlé Nigeria Plc, Abuja, AI and ML can be used to integrate sales, inventory, distribution, and supplier data to aid in managerial decision-making. But, they have to be integrated correctly, data quality must be appropriate and they need to be ready within the organisations. The literature highlights that, although the AI can generate insights faster, it can never be relied upon solely, and needs to be backed by human judgment, especially in unpredictable environments (Dohale et al., 2022; Dubey et al., 2021).

AI-Driven Predictive Analytics

Predictive analytics, powered by AI, enables firms to forecast potential outcomes based on historical and real-time data. This dimension emphasises the identification of patterns, correlations, and anomalies that can inform future operational decisions. For instance, AI-driven forecasting models can estimate consumer demand fluctuations, inventory requirements, and production bottlenecks in advance, reducing the risk of stock-outs or wastage (Chen et al., 2021). In multinational operations like Nestlé Nigeria Plc, this capability is particularly critical, given the scale of product lines, distribution channels, and the unpredictability of consumer behaviour post-pandemic. By projecting possible operational scenarios, predictive analytics can directly enhance the accuracy of decision-making, allowing managers to align production and distribution with real demand signals, rather than relying solely on historical averages or managerial intuition (Neiroukh et al., 2024).

Moreover, predictive analytics is not limited to supply-side operations; it extends to strategic planning and risk management. Firms can simulate various market and environmental conditions, estimate the impact of disruptions, and prepare contingency plans. Research during the COVID-19 era demonstrated that companies employing predictive analytics experienced more resilient operations and lower business risks, highlighting the value of foresight in complex, uncertain contexts (Drydakis, 2022; Khan, 2025).

AI-Based Decision Support Systems

Decision support systems (DSS) are the other dimension of AI/ML that can help managers by converting complex data into useful insights. DSS is more about using information to understand, prioritize and direct actions on the fly, while predictive analytics is more about predicting what will happen next. These systems provide dashboards, alerts, and scenario-based recommendations that enable timely decision-making on various aspects like procurement, logistics, and sales (Chen et al., 2021; Dubey et al., 2021). For Nestlé Nigeria Plc, DSS can enhance the speed of decision making, enabling managers to respond quickly to operational irregularities, track inventory levels or adjust distribution routes in response to sudden market changes.

The effectiveness of DSS depends on the human interpretation and acceptance of the organisation. The system allows for handling large volumes of data and identifying the best actions to take, but managers need to use their judgment when interpreting the recommendations based on the realities of their business. It is worth noting in the literature that DSS is especially useful in multinational companies where decision points are of large size and/or complexity for humans to process only by themselves (Dohale et al., 2022).

Concept of Operational Decision-Making

Operational decision making are the common, tactical decisions that organisations make to run their day-to-day business efficiently. It includes production scheduling, resource allocation, inventory management, logistics coordination, and immediate problem resolution. With supply chains being fragile and consumer behaviours being unpredictable in a post-pandemic era, operational decision-making is all about balancing responsiveness and reliability (Khan, 2025; Neiroukh et al., 2024). In Nestlé Nigeria Plc, the decision-making process has a direct impact on product availability, customer satisfaction, cost management, and overall efficiency.

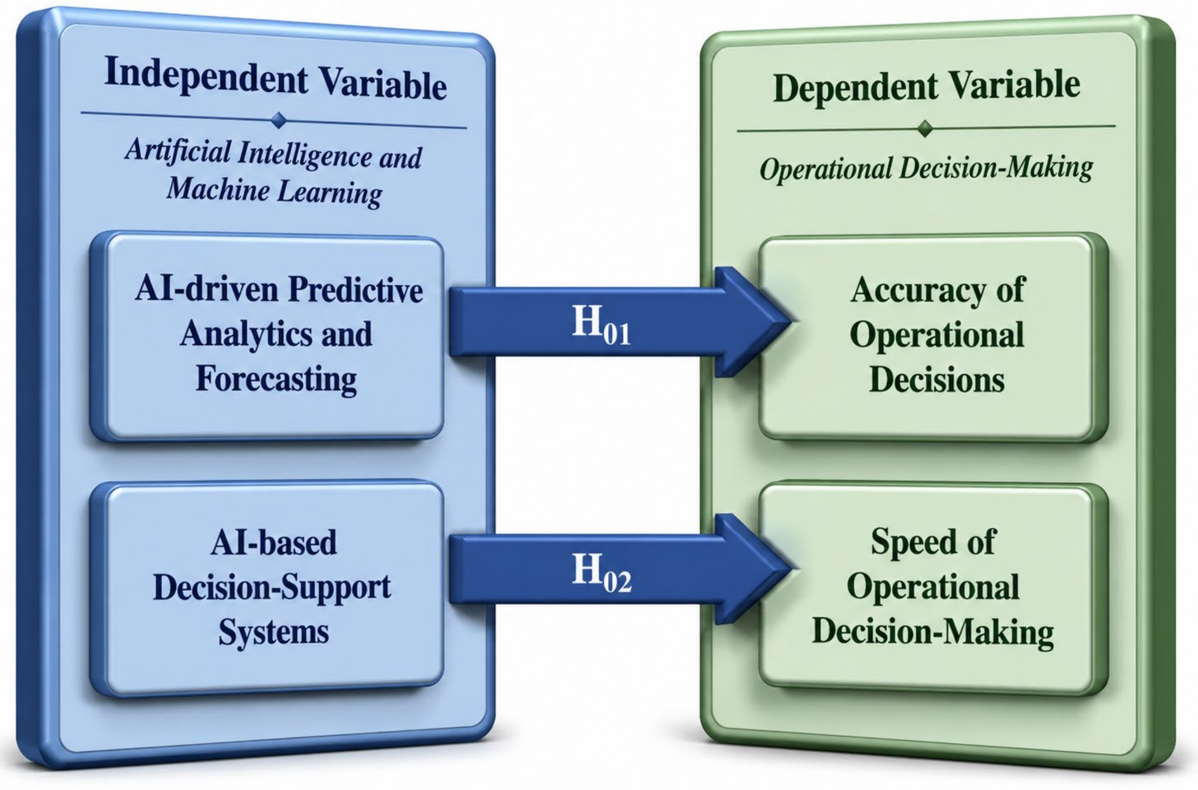
Understanding operational decision making is essential in two dimensions – accuracy and speed. Accuracy refers to the correctness, reliability and suitability of decisions, meaning that the operational plans are correctly designed in relation to the requirement and supply situation. Correct decisions result in fewer mistakes, less waste and and better organisation credibility. On the other hand, speed is about the timely decision making, which is the rapidity with which the manager will respond to any issues or opportunities that arise. Speed allows the organisation to make decisions that affect its operations in real time, which helps the company stay agile and responsive to market or supply chain changes. Speed enables the company to make decisions that impact its operations in real time, which allows the company to remain agile and responsive to sudden market or supply chain shifts (Dubey et al., 2021; Dohale et al., 2022). There is a close interdependence between both dimensions: a quick decision can fail if it is uninformed, and an informed decision can be worthless if it's made too late.

Theoretical Framework

The Dynamic Capabilities Theory is used as a theoretical lens for this study, as originally proposed by Teece, Pisano, and Shuen (1997), but transformed into the new AI/ML operational context after the pandemic. The key premise of this theory is that the competitive advantage can be created when an organisation has the ability to sense opportunities, seize them and transform operations. In other words, companies that have strong dynamic capabilities have the ability to rearrange their resources and processes when environmental changes occur, including fluctuations in demand or disruptions to their supply chains.

The theory has been criticized for its generality and lack of operationalisation as well as for being too abstract to be practically applicable. However, it is its focus on organizational adaptability, innovation, and resource reconfiguration, as key drivers of sustaining performance in a world of uncertainty, that are most important (Drydakis, 2022; Khan, 2025). In the context of this study, the concept of dynamic capabilities theory is applicable in understanding how Nestlé Nigeria Plc can harness AI-powered predictive analytics and AI-based DSS to improve the accuracy of decisions and quicken the decision-making process to adapt to the challenges facing its operations in the post-pandemic era. The theory offers a frame of reference for analyzing the implications of technology adoption for successful operational routines, which resonates with the study's goal of connecting AI/ML features to management decisions.

Conceptual Framework



Source: Researcher's Conceptualisation (2026)

The conceptual diagram presents the hypothesised relationship between Artificial Intelligence and Machine Learning and operational decision-making in Nestlé Nigeria Plc. It shows Artificial Intelligence and Machine Learning as the independent variable, represented by two dimensions: AI-driven predictive analytics and forecasting, and AI-based decision-support systems. The first protruding arrow, labelled **H_{01}**, connects predictive analytics and forecasting to the accuracy of operational decisions, indicating that the study will test whether forecasting tools significantly influence the correctness, reliability, and evidence-based nature of operational decisions. The second protruding arrow, labelled **H_{02}**, connects AI-based decision-support systems to the speed of operational decision-making, showing that the study will examine whether AI-supported dashboards, alerts, recommendations, and analytical tools significantly improve how quickly managers interpret information and respond to operational issues. Overall, the diagram clearly reflects the study's focus on how AI and machine learning capabilities may shape decision accuracy and decision speed in a post-pandemic operational environment.

Empirical Review

Neiroukh et al. (2024), among others, studied the effect of the capability of artificial intelligence within an organization on performance in an international setting in the Middle East. They used a quantitative research design and surveyed 210 managers with stratified random sampling from several sectors through questionnaires and analysed the data using structural equation modelling (SEM). The study found that AI capability played a significant mediating role in the organizational decision-making process, which could positively impact strategic and operational outcomes. They suggested a systematic implementation of AI at various levels of decision-making, aiming to enhance performance across organizations. A limitation of the study is its regional focus, and the use of self-report measures that could impact the generalisability and response bias.

To boost efficiency of communication and decision making in large organizations in Bangladesh, Nijhum (2025) studied AI-driven models of digitization. The study adopted a descriptive design with a survey approach and involved 150 respondents who were selected using purposive sampling. The data were collected using a structured questionnaire and the data were analyzed using regression analysis. The results showed that models of digital transformation based on AI enable faster decision-making and more efficient inter-department communication. The author suggested that companies consider gradual implementation across the various functions. Some limitations were narrow industrial scope and possible technology familiarity bias among the respondents.

Nasseef et al. (2021) investigated AI in Public Health Care Systems of Saudi Arabia to facilitate Knowledge Sharing and Decision Making between the government. Using a mixed methods approach, 120 healthcare administrators were interviewed and surveyed, thematically coded and analysed using regression. Results showed that the use of AI in knowledge management had a positive impact on the efficiency and accuracy of making operational decisions for public health interventions. They suggested that the results should be generalised more broadly within the regional health system and commented on the small number of samples and contextual generalisability.

In Europe, Dubey et al. (2021) studied the use of AI for supply chain analytics in B2B companies in the pandemic. A questionnaire was designed and administered, and a cross-sectional survey with stratified sampling of 180 supply chain managers was conducted, followed by the analysis of the results using partial least squares structural equation modeling. The data showed AI analytics helped in quicker decision-making and resilience on the supply chain side of disruption. They recommended enhancing the synergy of collaboration between organizations with the best possible use of AI. A major limitation of the study was that it was cross sectional and therefore causal inferences could not be made.

In Singapore, Chen et al (2021) tested a human-centric AI decision support framework for predictive maintenance in industrial asset management. Using a quasi-experimental design with 90 participants, data was collected via system logs and questionnaires, and analysed using descriptive statistics and ANOVA. They discovered that AI decision support played a crucial role in better speed and accuracy of operation maintenance decisions – they believe that it should be incorporated into regular asset management. The limitations of the study were industry and observation period.

Using the framework of the dynamic capabilities, Drydakis (2022) explored the role of AI in mitigating business risks in SMEs in Greece in the context of COVID-19. The study used convenience sampling of 130 SME managers and analysed the data using regression techniques. The results revealed that the implementation of AI enhanced risk assessment, decision accuracy, and adaptability of responses. Recommendation: Creation of specific AI solutions for SMEs, but limited applicability in other contexts/other firms.

Jhamb (2022) discussed the effects of AI and big data analytics on the supply chain during the COVID-19 pandemic in different regions. Through a systematic literature review (SLR) process, 85 studies were identified and results indicated that AI implementation has contributed to enhanced operational decision-making, resilience and sustainability. They suggested that organizations should adopt AI-powered predictive and prescriptive analytics to improve performance, but also highlighted the challenges of there being little empirical evidence to support this and studies being focused in one geographic area.

The study by Dohale et al. (2022) explored the use of AI in production resilience in the manufacturing sector during the Covid19 pandemic in India. Data was analysed with SEMs using 200 operations managers from the purposive sampling design. They said that the operational responsiveness, predictive maintenance, and decision speed were all improved by AI tools. Organisational training and integration of AI systems were recommended, and a drawback was that the data relied on self-report and was sector-specific.

Khan, (2025) used descriptive survey method to study the role of AI and ML in optimizing operational decision making after COVID-19 in Nigeria with 160 managers sampled in FMCG sectors from various firms across Nigeria using stratified random sampling technique. Questionnaires were used to gather data which was then analysed using regression and correlation analysis. The study revealed that the use of predictive analytics increased decision accuracy, and AI decision support increased decision speed; it recommended greater integration of AI in the operational workflow. The limitations were the focus on a single sector and the cross-sectional data, making causal interpretations difficult.

Using a comprehensive literature review of 120 articles, Aylett-Bullock et al. (2020) identified applications of AI around the world in relation to COVID-19. They found that AI was used in the fields of epidemiological forecasting, resource allocation, and operational management within healthcare and supply chain operations. They suggested the need for AI to be incorporated into the response mechanism for crises, and that there were constraints due to the rapid changing nature of the pandemic and the variance in AI deployments around the world.

Literature Gap

Although many studies have been conducted during and post the pandemic on the applications of AI and machine learning in decision-making, most of the studies have been conducted in a context of the broad organisation or healthcare or manufacturing sector, and have looked at AI capability, digital transformation, or supply chain analytics separately (Dubey et al., 2021; Nijhum, 2025; Neiroukh et al., 2024). Though it was established that predictive analytics using

AI tools could reduce the error rate in decision-making, and decision support systems based on AI could accelerate decision-making, there were few studies that explicitly connected these two dimensions to the operational decision-making process in a single multinational enterprise (MNE) in a developing country context, for example, Nestlé Nigeria Plc, Abuja. In addition, the majority of empirical studies were based on self-reported perceptions or cross-sectional surveys, and the use of AI/ML in the field to observe operational outcomes in real time is limited, leaving a lack of understanding about the real-world impact of these technologies on decision accuracy and speed. Additionally, the lack of empirical studies in post-pandemic contexts that directly link the use of these AI elements to measurable operational performance outcomes in EM countries is significant, underscoring the need for more context-specific studies to uncover the relationship between predictive analytics, decision-support systems and operational performance gains, especially for multinational corporations in EM countries (Khan, 2025; Dohale et al., 2022). Overcoming this challenge will yield insights into how organizations such as Nestlé Nigeria Plc can leverage AI and ML for improved operational efficiency and responsiveness.

3. METHODOLOGY

Using descriptive research design enabled the researcher obtain a realistic picture of the context of the organisation, as there was no manipulation of variables, and the information collected and analyzed were sufficient to explain the impact of AI and machine learning on operational decision making in the study. The study population consisted of 496 employees across the organisation, including managers and staff directly involved in the decision-making process, such as production managers, officers in the supply chain, inventory controllers, logistics coordinators, and others who regularly interacted with AI-driven predictive analytics and AI-based decision-support systems. The sample size was calculated as follows: sample size (n) = N / [1 + N(e)^2] where N = 496 and e = 0.05, and the sample size was then increased by 20% to allow for non-responses and incomplete questionnaires, giving an effective sample size of 269 respondents. Stratified sampling was used to make sure that each operational level was represented proportionately to increase the accuracy and generalisability of the results. Structured questionnaire was used to collect the primary data which focused on capturing the information on the independent variables (AI-driven predictive analytics and AI-based decision-support systems) and on the dependent variable (operational decision-making: accuracy and speed). The internal consistency of the four constructs was evaluated using

Cronbach's α, resulting in high values ranging from 0.80 to 0.87 for the four constructs, respectively, AI-driven predictive analytics, AI-based decision-support systems, decision accuracy, and decision speed, which indicates high internal consistency. Content validation was conducted by experts in AI applications and operational management to establish the validity. In this study, data analysis was performed using regression analysis in SPSS version 27, with the regression models for each hypothesis as follows: for H_{01}, Decision Accuracy = $\beta_0 + \beta_1$(Predictive Analytics) + ε, and for H_{02}, Decision Speed = $\beta_0 + \beta_2$(Decision Support Systems) + ε, where the individual variables represent the specific dimensions of AI/ML, and ε denotes the error term.

4. DATA PRESENTATION, ANALYSES AND INTERPRETATION

Result and Discussion

Table 1: Administered Questionnaire

	Number	Percentage
Questionnaire Distributed	265	100%
Returned Questionnaire	227	86%
Unreturned Questionnaire	38	14%

Source: Field Survey, (2026)

Table 1 indicates a 86% return of the 265 questionnaires sent out to the staff of Nestlé Nigeria Plc, Abuja while 38 questionnaires were not collected, representing 14% non-response. This showed that the respondents were very active as it increased the credibility and representativeness of the study. This left the impression that most of the managerial and operational personnel who play a direct role in AI-based predictive analytics and decision-support systems actively inputted data into them for analysis, thus ensuring their data provided a reliable set of data on which to examine the effects of AI and machine learning on the organization's operational decision-making. Although the non-response rate was small (14%), the data appeared adequate for making accurate inferences and conclusions about decision accuracy and speed, with possible limitations in the ability to reach a small portion of the population.

Test of Hypotheses

Testing of Hypothesis One

H_{01}: Predictive analytics and forecasting have no significant effect on the accuracy of operational decisions at Nestlé Nigeria Plc.

Model 1

DA= $\alpha + \beta_1 PA + + \varepsilon$...1

Table 2 **Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.734[a]	.538	.536	.36254

a. Predictors: (Constant), PA

***Source**: SPSS Output Version 27.0.1*

The model summary of the relationship between predictive analytics and forecasting, and accuracy of operational decisions at Nestlé Nigeria Plc is presented in Table 2. The outcome indicated a strong positive correlation between predictive analytics and decision accuracy with an R of .734. The R Square value of 0.538 indicated that predictive analytics and forecasting explains 53.8% of the variability in the correctness of operational decisions, with the rest being explained by other factors that were not measured in the model. The model's adjusted R Square value of .536 also supported the excellent explanatory power of the model. This meant that predictive analytics and forecasting was a critical element to enhance the accuracy of operational decisions made in Nestlé Nigeria Plc.

Table 3 **ANOVA[a]**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	34.478	1	34.478	262.315	.000[b]
	Residual	29.573	225	.131		
	Total	64.051	226			

a. Dependent Variable: DA
b. Predictors: (Constant), PA

***Source**: SPSS Output Version 27.0.1*

The ANOVA result to assess the overall significance of the regression model is presented in Table 3. The obtained F value was 262.315 with a significance value of .000 which is less than the 0.05 level of significance. This meant that the regression model was statistically significant, and that predictive analytics and forecasting had a significant impact on the accuracy of operational decisions. It was suggested that the application of predictive analytics in forecasting demand, developing operational patterns and in decisions for planning had a significant impact on improving operational decision making in Nestlé Nigeria Plc.

Table 4 **Coefficients[a]**

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	T	Sig.
1	(Constant)	1.120	.182		6.157	.000
	PA	.744	.046	.734	16.196	.000

a. Dependent Variable: DA

***Source**: SPSS Output Version 27.0.1*

Table 4 depicted the coefficient result which indicated the specific effect of predictive analytics and forecasting on decision accuracy. The coefficient value of .744 showed that a 1-unit increase in predictive analytics and forecasting resulted in a .744 unit change or improvement in the accuracy of operational decisions. This effect was statistically significant with the t value of 16.196 and significance value of .000. Hence, the null hypothesis which indicated that predictive analytics and forecasting does not significantly affect the accuracy of the operational decisions at Nestlé Nigeria Plc, was rejected. This meant that predictive analytics and forecasting had a huge impact on the decision making process, making more informed and accurate operational decisions that were backed by evidence and made in time.

Testing of Hypothesis Two

H_{02}: AI-based decision-support systems have no significant effect on the speed of operational decision-making at Nestlé Nigeria Plc.

DS= $\alpha + \beta_1 DSS + \varepsilon$...3.3

Table 5 **Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.636[a]	.405	.402	.41035

a. Predictors: (Constant), SMM

***Source**: SPSS Output Version 27.0.1*

The model summary for the regression analysis of the effect of the AI based decision support systems on the speed of operational decision making at Nestlé Nigeria Plc was presented in Table 5. The R value of .636 showed a strong positive relationship between the IV and the decision speed and the R Square value of .405 indicated that AI-based decision-support systems accounted for 40.5% of the variance in decision speed with remaining unexplained variance is attributed to other unexplored factors. The R square (adjusted) value of .402 indicated that the model is strong in explaining the independent variable.

Table 6 **ANOVA**[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	25.759	1	25.759	152.975	.000[b]
	Residual	37.888	225	.168		
	Total	63.647	226			

a. Dependent Variable: DS
b. Predictors: (Constant), DSS

***Source**: Generated using SPSS Version 27.0.1*

The ANOVA results showed that the F-value was 152.975 and the significance level was .000 (which is less than .05), indicating that the regression model was statistically significant. This suggested that the model was appropriate to assess the hypothesised relationship, as AI-based decision-support systems had a meaningful impact on the speed of operational decision making.

Table 7 **Coefficients**[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.689	.185		9.141	.000
	DSS	.573	.046	.636	12.368	.000

a. Dependent Variable: DS

***Source**: Generated using SPSS Version 27.0.1*

The coefficient analysis was provided in Table 7, and the coefficient for AI-based decision-support systems was .573, the t-value was 12.368 and the significance level was .000. This suggested a .573 unit increase in decision speed for every unit increase in the adoption of AI-based decision support systems, thus confirming a significant positive effect. Based on this, the null hypothesis H_{02} was rejected, as it had suggested that there was no significant difference between the use of AI-based decision support systems and operational decision-making. The results indicated that the use of AI-based decision support systems significantly improved the management response to events and timeliness of decisions made in Nestlé Nigeria Plc.

Discussion of Findings

The findings were discussed and it was found that the null hypothesis H_{01} which stated that there was no significant relationship between predictive analytics and forecasting in the accuracy of making operational decision at Nestlé Nigeria Plc was rejected. The analysis showed that the use of predictive analytics had a positive impact on the accuracy of decisions, highlighting that those who used AI-driven predictive tools were more likely to make informed and accurate operational decisions. This discovery was consistent with previous research by Neiroukh et al. (2024) and Khan (2025) which indicated that the use of AI in decision-making processes and operational performance led to improved forecasting accuracy and early detection of operational bottlenecks. Likewise, Dubey et al. (2021) and Chen et al. (2021) established that predictive analytics aids in planning and helps minimize the mistakes in supply chain and manufacturing processes respectively. On the other hand, although Nijhum (2025) stated that AI has a positive effect on decision accuracy, Nasseef et al. (2021) reported that the quality of the data and the integration of the system sometimes not only limits the outputs of AI in Healthcare but also challenges the study, suggesting that AI's impact varies based on contextual factors. The result was also validated by the Dynamic Capabilities Theory that states that companies become more competitive by having the capability to sense, seize, and transform to adapt to environmental changes, and here, predictive analytics is interpreted as a sensing and seizing tool which increases the accuracy of operational decisions (Drydakis, 2022; Jhamb, 2022).

The same applies to H_{02}, which suggested that AI decision support systems did not significantly affect the decision-making speed in the operations. Regression results showed that decision-support systems had a significant positive impact on the timeliness of managerial decisions, suggesting that real-time dashboards, alert and recommendation systems helped to execute decisions quickly. This echoes the work of Dohale et al. (2022) and Aylett-Bullock et al. (2020), who found that AI-powered decision support systems made a significant contribution to responsiveness both before and after the pandemic in production and healthcare operations. Similarly, Chen et al. (2021) found that operational maintenance tasks delays were decreased with the presence of human-centric AI decision-support frameworks. While the current results are limited, some are somewhat at odds with the results of Comito and Pizzuti (2022) who warned that user familiarity and organisational culture may limit the effectiveness of system adoption. This was supported by the theoretical background of Dynamic Capabilities Theory, which emphasises that AI-driven decision-support systems are indeed dynamic capabilities that enable the firm to quickly address operational problems, thereby enhancing decision speed and organisational agility (Neiroukh et al., 2024; Khan, 2025).

Taken together, these results confirm that AI-based predictive analytics and AI-based decision support systems clearly enhance decision-making at Nestlé Nigeria Plc, both theoretically and empirically, but a number of contextual limitations mentioned in the literature should be considered to avoid the overgeneralisation of the results.

5. CONCLUSION AND RECOMMENDATIONS

Conclusion

The study concluded that both AI-driven predictive analytics and AI-based decision-support systems significantly influenced operational decision-making at Nestlé Nigeria Plc, with predictive analytics enhancing decision accuracy and decision-support systems improving decision speed. These findings underscored the importance of integrating AI technologies into managerial processes to optimise operational efficiency and responsiveness.

Recommendations:

i. Nestlé Nigeria Plc should invest further in the development and integration of AI-driven predictive analytics tools to enhance the accuracy of operational planning and resource allocation.

ii. The organisation should implement and train staff on AI-based decision-support systems to ensure faster, real-time operational decision-making, improving responsiveness to market and supply chain fluctuations.

REFERENCES

Aylett-Bullock, J., Luccioni, A., Pham, K., Lam, C., & Luengo-Oroz, M. (2020). Mapping the Landscape of Artificial Intelligence Applications against COVID-19. *ArXiv, abs/2003.11336*. https://doi.org/10.1613/jair.1.12162.

Bansal, A., Padappayil, R., Garg, C., Singal, A., Gupta, M., & Klein, A. (2020). Utility of Artificial Intelligence Amidst the COVID 19 Pandemic: A Review. *Journal of Medical Systems, 44*. https://doi.org/10.1007/s10916-020-01617-3.

Chen, J., Lim, C., Tan, K., Govindan, K., & Kumar, A. (2021). Artificial intelligence-based human-centric decision support framework: an application to predictive maintenance in asset management under pandemic environments. *Annals of Operations Research*, 1 - 24. https://doi.org/10.1007/s10479-021-04373-w.

Comito, C., & Pizzuti, C. (2022). Artificial intelligence for forecasting and diagnosing COVID-19 pandemic: A focused review. *Artificial Intelligence in Medicine, 128*, 102286 - 102286. https://doi.org/10.1016/j.artmed.2022.102286.

Debnath, S., Barnaby, D., Coppa, K., Makhnevich, A., Kim, E., Chatterjee, S., Tóth, V., Levy, T., Paradis, M., Cohen, S., Hirsch, J., Zanos, T., Becker, L., Cookingham, J., Davidson, K., Dominello, A., Falzon, L., McGinn, T., Mogavero, J., & Osorio, G. (2020). Machine learning to assist clinical decision-making during the COVID-19 pandemic. *Bioelectronic Medicine, 6*. https://doi.org/10.1186/s42234-020-00050-8.

Dohale, V., Akarte, M., Gunasekaran, A., & Verma, P. (2022). Exploring the role of artificial intelligence in building production resilience: learnings from the COVID-19 pandemic. *International Journal of Production Research, 62*, 5472 - 5488. https://doi.org/10.1080/00207543.2022.2127961.

Drydakis, N. (2022). Artificial Intelligence and Reduced SMEs' Business Risks. A Dynamic Capabilities Analysis During the COVID-19 Pandemic. *Information Systems Frontiers, 24*, 1223 - 1247. https://doi.org/10.1007/s10796-022-10249-6.

Dubey, R., Bryde, D., Blome, C., Roubaud, D., & Giannakis, M. (2021). Facilitating artificial intelligence powered supply chain analytics through alliance management during the pandemic crises in the B2B context. *Industrial Marketing Management, 96*, 135 - 146. https://doi.org/10.1016/j.indmarman.2021.05.003.

Gawande, M., Zade, N., Kumar, P., Gundewar, S., Weerarathna, I., & Verma, P. (2025). The role of artificial intelligence in pandemic responses: from epidemiological modeling to vaccine development. *Molecular Biomedicine, 6*. https://doi.org/10.1186/s43556-024-00238-3.

Hasan, M., Islam, M., Sadeq, M., Fung, W., & Uddin, M. (2023). Review on the Evaluation and Development of Artificial Intelligence for COVID-19 Containment. *Sensors (Basel, Switzerland), 23*. https://doi.org/10.3390/s23010527.

Jhamb, S. (2022). Mapping the Potential Supply Chain Impressions of the COVID-19 (SARS-CoV-2) Pandemic on Artificial Intelligence and Big Data Analytics: A Sustainability Framework and Programmatic Research Review With Deep Learning Approaches. *Journal of Strategic Innovation and Sustainability*. https://doi.org/10.33423/jsis.v17i2.5397.

Khan, F. (2025). The Role of Artificial Intelligence and Machine Learning in Optimizing Operational Decision-Making Post-Pandemic. *International Journal For Multidisciplinary Research*. https://doi.org/10.36948/ijfmr.2025.v07i03.41483.

Lv, C., Guo, W., Yin, X., Liu, L., Huang, X., Li, S., & Zhang, L. (2024). Innovative applications of artificial intelligence during the COVID-19 pandemic. *Infectious Medicine, 3*. https://doi.org/10.1016/j.imj.2024.100095.

Nasseef, O., Baabdullah, A., Alalwan, A., Lal, B., & Dwivedi, Y. (2021). Artificial intelligence-based public healthcare systems: G2G knowledge-based exchange to enhance the decision-making process. *Gov. Inf. Q., 39*, 101618. https://doi.org/10.1016/j.giq.2021.101618.

National Bureau of Statistics. (2024). *CPI and inflation report June 2024*. https://www.nigerianstat.gov.ng/elibrary/read/1241533

Neiroukh, S., Emeagwali, O., & Aljuhmani, H. (2024). Artificial intelligence capability and organizational performance: unraveling the mediating mechanisms of decision-making processes. *Management Decision*. https://doi.org/10.1108/md-10-2023-1946.

Nijhum, A. (2025). Artificial Intelligence-Driven Digital Transformation Models for Enhancing Organizational Communication and Decision-Making Efficiency. *American Journal of Scholarly Research and Innovation*. https://doi.org/10.63125/8qqmrm26.

Rajagopal, N., Qureshi, N., Durga, S., Asis, E., Soto, R., Gupta, S., & Deepak, S. (2022). Future of Business Culture: An Artificial Intelligence-Driven Digital Framework for Organization Decision-Making Process. *Complexity, 2022*. https://doi.org/10.1155/2022/7796507.

Shrestha, Y., Ben-Menahem, S., & Von Krogh, G. (2019). Organizational Decision-Making Structures in the Age of Artificial Intelligence. *California Management Review, 61*, 66 - 83. https://doi.org/10.1177/0008125619862257.

Syrowatka, A., Kuznetsova, M., Alsubai, A., Beckman, A., Bain, P., Craig, K., Hu, J., Jackson, G., Rhee, K., & Bates, D. (2021). Leveraging artificial intelligence for pandemic preparedness and response: a scoping review to identify key use cases. *NPJ Digital Medicine, 4*. https://doi.org/10.1038/s41746-021-00459-8.

Van Der Schaar, M., Alaa, A., Floto, A., Gimson, A., Scholtes, S., Wood, A., McKinney, E., Jarrett, D., Liò, P., & Ercole, A. (2020). How artificial intelligence and machine learning can help healthcare systems respond to COVID-19. *Machine Learning, 110*, 1 - 14. https://doi.org/10.1007/s10994-020-05928-x.